Improved Detection and Ambiguity Resolution of Multiple Targets in MPRF Radar

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Abstract

This paper presents the results of an investigation into the mechanisms that generate ghost targets when many real targets are present on the same azimuth in a MPRF radar system. A new PRI selection strategy is proposed as a method to eliminate these ghost targets. The use of evolutionary algorithms as a means of optimising the PRI selection is discussed.

1. Introduction

This paper presents an overview of an investigation that has been conducted into the formation of ghost targets in range and/or velocity ambiguous radar systems when many targets are on the same azimuth.

The results of the investigation have led to the development of a new PRI schedule strategy that will allow the probability of ghost targets forming tracks to be reduced to a negligible value.

Section 2 introduces medium PRF radar and section 3 details the process of ambiguity resolution. Section 4 discusses the generation of ghosts from multiple targets and their ability to form tracks. Section 5 describes a method of decorrelating the ghost returns thus minimising the formation of ghost tracks. Section 6 discusses the results of previous work on the use of Evolutionary Algorithms in optimisation of MPRF PRI sets and their particular applicability to the generation of multiple sets of PRIs. Section 7 concludes.

2. Medium PRF Radar

Medium PRF radar systems were devised as a compromise between Low and High PRF systems and allow all-round measurements of both the range and Doppler of targets in high clutter environments to be made.

By operating above the low-PRF region, the ambiguous repetitions of the mainbeam clutter spectrum may be sufficiently separated without incurring unreasonable range ambiguities. Consequently, the radar is better able to reject mainbeam clutter through Doppler filtering without rejecting too many targets.

By operating below the high-PRF region, the radar's ability to contend with sidelobe clutter in tailchase engagements is improved. Targets may be extracted from sidelobe clutter using a combination of Doppler filtering and range gating.

A significant issue which affects many look-down airborne radars is the difficulty in distinguishing between unwanted ground moving targets and targets of interest with low closing rates. Commonly these unwanted targets are readily detectable, but must be excluded (for example, by Doppler filtering) to keep the ambiguity resolution problem within bounds.

An excellent review of medium PRF radar and PRF selection is provided by Long and Harringer [1].

Such radars use waveforms that are ambiguous in range, Doppler or both. Existing techniques that resolve these ambiguities require the number of detections input to the ambiguity resolution process to be kept to a small number, as otherwise the number of false correlations (‘ghosts’) becomes unworkably large.

In commonly used methods of track formation, target returns that cross a detection threshold are taken as ‘potential targets’. As the information from the received signal is limited, a false alarm must be treated as a true target, until it can be established as false. A high false alarm rate causes problems with the association of returns with tracks and leads to an excessive number of false tracks being reported with the consequent risk of the tracking system becoming overwhelmed.

3. MPRF Ambiguity Resolution

Since MPRF radar systems use waveforms that are inherently ambiguous in range, Doppler or both the true target range is often beyond the unambiguous range, the range at which the echo from a target returns in a time less than the interval between transmitter pulses. In many cases the range is greater than several multiples of the unambiguous range. Doppler measurements may also be aliased and the true Doppler frequency may be several times beyond the Shannon limit. This means that a range measurement, ΔR, is the remainder after dividing the true range by the unambiguous range and is ambiguous since it can be interpreted as originating at many possible ranges. In essence, for each range measurement, along an azimuth spoke there are multiple potential targets at ranges given by the expression

$$R = nR^u + \Delta R$$

where R is the true range of the target, R^u is the maximum unambiguous range of the radar at the PRF in use and n = 0,1,2,…. All ranges are expressed as an integer numbers of range bins.

Similar expressions exist for Doppler shift but as the methods of resolving Doppler ambiguities are the same as those for range ambiguities only methods for range will be described.

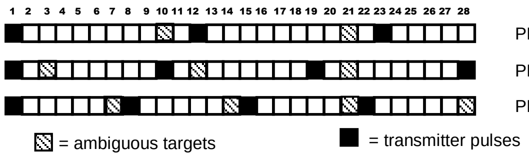
Existing techniques to resolve range ambiguities are based on the Chinese Remainder Theorem either by direct computation by the use of the Chinese Remainder Algorithm or the Coincidence or Unfolding Algorithm.

Conventionally, the Chinese Remainder Algorithm has employed pulse repetition intervals (PRI = 1/PRF) of integer numbers of range cells and subsequent modulo arithmetic which is sufficiently simple to enable a hardware solution [2]. However, integer mathematics imposes limitations on the number of suitable PRFs and does not address the minimisation of blind zones. The coincidence algorithm is more computationally intensive for small numbers of targets but removes certain constraints on the PRF selection.

3.1 The Chinese Remainder Theorem and the Coincidence Algorithm

The method of solution is based on the Chinese remainder theorem which is said to have been used to count the size of the ancient Chinese armies (i.e., the soldiers would split into groups of 3, then 5, then 7, etc, and the “left-over” soldiers from each grouping would be counted).

In the radar case several PRIs are used each of which has an unambiguous range that is a prime, or co-prime with the other members of the set, number of range bins. The product of all the numbers of range bins, i.e., the individual unambiguous ranges, in each set of PRIs is made equal to or greater than the maximum range (unambiguous) of the radar. The ambiguity resolution is performed after the CFAR detector and thus uses target present/target absent data.



In PRF1 the target is seen in range cells 10, 21, 32, 43, 54 etc..
In PRF2 the target is seen in range cells 03, 12, 21, 30, 39, 48 etc…
In PRF3 the target is seen in range cells 07, 14, 21, 28, 35, 42 etc.…
The only common value is **21** so this must be the true range.

Fig 1. Coincidence Algorithm for Single Target

The system of equations is solved by unfolding all the possible ranges, known as the feasible solutions, and finding the range that is common to all sets of PRIs as illustrated in Figure 1. This is known as the Coincidence Algorithm and the Chinese Remainder Theorem [3, 4] guarantees that this solution is unique within the maximum unambiguous range of the radar.

The solution may also be represented graphically in the form of a Venn Diagram [5]. The solution is the intersection of all the sets of feasible solutions

A convenient and general method of assessing the decodability of a multiple-MPRF waveform allowing for measurement errors is described by Kinghorn [6].

In practice, because of blinding and problems of target detection it is normal to make the product of a smaller number of range bins than the full set of PRIs exceed the required system unambiguous range. This leads to what is known as an *M* from *N* scheme.

3.2 The Chinese Remainder Theorem and Ghosting in the Presence of Multiple Targets

A simple case of multiple targets on the same azimuth will now be considered. If there are *T* targets on the same azimuth then *T* returns will be taken in each PRI. This means that there will now be more than one ambiguous target return in each individual PRI interval.

For two targets and two PRIs there are four equations to be solved and since it is not possible to associate the individual returns measured within a given PRI with the individual targets four equations result. The Chinese Remainder Theorem guarantees that there are solutions to all these equations and there are four results. Two results represent two true target positions and two represent ghosts. Examination of the mathematical relationship between the two true target positions and their ghosts shows that the positions are conjugate. It is thus not possible to determine unambiguously the range of two targets using only two PRIs.

For more than two targets the equations are formed by simple combination it is easy to show that the number of solutions is T^M where M is the number of PRIs and T is the number of targets.

Since there are T true targets the number of ghosts is found by subtraction

$$T^M - T = T\left(T^{M-1} - 1\right)$$

From the above it is clear that the number of ghosts likely to be present increases very rapidly with only a small increase in the number of strong targets present.

In the case of more than two true targets the set of solutions appears to form an 'orbit' in that any of the true positions and ghosts are interchangeable. It is thus not possible to distinguish which are true targets and which are ghosts.

The number of ghosts generated per scan is invariant and is a function of the number of targets simultaneously on the same azimuth, however observation shows that this number is not always apparently present. Non visibility of ghosts may be caused by some ghosts being coincident with true targets or other ghosts. Alternatively, in the case of an *M* from *N* scheme, the 'missing' ghosts may lie outside the range of interest.

A more comprehensive mathematical treatment of the formation of ghosts is contained in [7]

4. The formation of Ghost Tracks

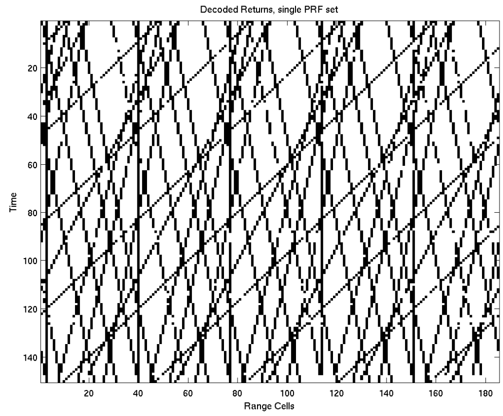


Figure 2. Ghost Tracks from 10 Targets with ambiguities resolved using two PRIs

Figure 2 shows the range-time plot from 10 targets viewed with a 2 PRI system. The 10 targets are: two closing targets with equal velocities; four opening targets with equal velocities; three closing targets with differing velocities plus one stationary target. The PRIs are such that the ambiguity is approximately five times in range.

Severe ambiguity can clearly be observed and as all the ghosts are strong, it is very difficult to determine which tracks are from the real targets. As the probability of detection is 100%, some of the ghost tracks can be identified as they have brief breaks and can be dismissed, but this is a special case. In general, with targets in close formation, the ghosts will appear to move in a very ‘target-like’ manner.

5. Decorrelation of Ghost Tracks

The effect of changing the PRI set on a scan to scan basis has been investigated. Five sets of two PRIs were cycled through. The effect is shown in Figure 3 The true tracks are clearly visible against a background of track fragments caused by ghosting. Although approximately the same number of ghosts are present, they occur in a different location for each PRI set, therefore the effect of the PRI changes has been to decorrelate the ghost tracks.

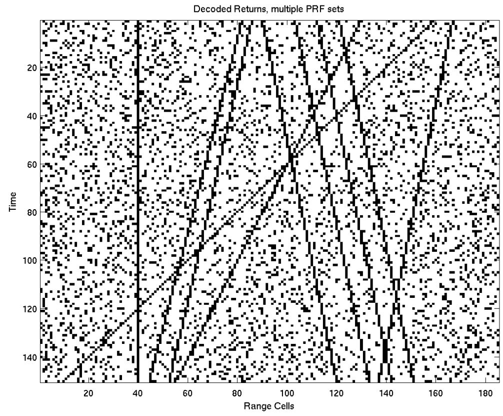


Fig 3. Effect of Scan to Scan PRF Change

Visual inspection indicates a clear set of true target tracks and suggests that a high score would be achieved on such SIAP metrics as accuracy, completeness, continuity and clarity. Unfortunately, the ghost target returns must still be handled by the tracker, and so a tracking system capable of handling a very high false alarm rate must be used. Such a tracker has been developed as an earlier part of the program and is described in [8]

To improve angular resolution, often the *M* of *N* processing is performed on a cyclic basis with the last PRI being decoded with the previous *N*-1, rather than waiting for *N* new PRIs to be transmitted and decoded as a block. The requirement for a change in the PRI set could make decoding using a rolling PRI scheme more difficult as to allow a rolling system, the PRIs must be intra-set decodable as well as inter-set decodable.

6. PRI Set Selection Using Evolutionary Algorithms

The new requirement for several sets of PRIs presents a problem in that there is no simple method of generating PRF sets. A scheme based on the coincidence algorithm and utilising a near continuous range of PRFs creates a vast search space which enables multiple PRI sets with superior solutions to be found [9].

Since an exhaustive search of PRF combinations is not possible, evolutionary algorithms have been employed. PRF set selection is made on the basis of resolving ambiguities, removing blind velocities and minimising blind zones in the range/velocity space [9].

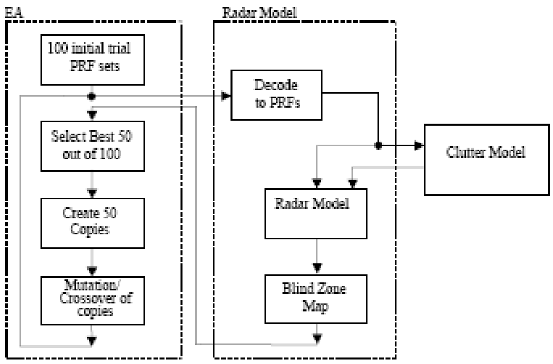


Figure 4. Flowchart of the Optimisation Process

Evolutionary Algorithms are optimisation procedures which operate over a number of cycles (generations) and are designed to mimic the natural selection process through evolution and survival of the fittest [10], [11].

A *population* of *M* independent individuals is maintained by the algorithm, each individual representing a potential solution to the problem, in this case a PRI set. Each individual has one *chromosome*. This is the genetic description of the solution and may be broken into *n* sections called *genes*. Each gene represents a single parameter in the problem, for example a PRI, therefore a problem that has eight unknowns for example, would require a chromosome with eight genes to describe it.

The three simple operations found in nature, natural selection, mating and mutation are used to generate new chromosomes and therefore new potential solutions. In the technique employed by Cranfield new chromosomes were generated by a combination of mating (otherwise known as *crossover*) and applying random variation in the form of Gaussian noise, with a standard deviation that reduced with each generation, to each gene in each chromosome. Each chromosome is evaluated at every generation using an *objective function* that is able to distinguish good solutions from bad ones and to score their performance.

With each new generation, some of the old individuals die to make room for the new, improved offspring. Despite being very simple to code, requiring no directional or derivative information from the objective function and being capable of handling large numbers of parameters simultaneously, evolutionary algorithms can achieve excellent results. A flowchart representing the whole process is given in Figure 4. The radar model accepts a chromosome from the evolutionary algorithm and decodes it into a set of PRIs. Operational parameters are passed to the clutter model, which in turn returns clutter data. A blind zone map is created and target visibility is determined. The raw visibility data is then passed back to the evolutionary algorithm as the objective value to drive the evolutionary process. A new generation of PRFs is then produced and the process repeated until a satisfactory convergence has been achieved.

The use of the coincidence algorithm permits PRIs to be selected with the resolution of the clock period. This improved resolution increases the number of available PRIs but enables selection to be optimized for decodability, blindness, blind velocities, and ghosting.

The evolutionary algorithm can select near-optimal PRF sets efficiently, with modest computing effort and produce a significant improvement in radar detection performance. The “quality” of each set is based on models of airborne fire control radar and associated clutter and so each PRF set is application/scenario specific.

Repeated runs of the algorithm identify near-optimal PRF sets which differ marginally from each other indicating the existence of several similar local optima and the ability of the evolutionary algorithm to find them.

It is this ability to find many near optimal PRI sets that makes the use of Evolutionary Algorithms an essential means to implementing multiple PRI sets to overcome ghosting in MPRF radar.

7. Conclusions

This paper has outlined the theory surrounding the decoding of a set of ambiguous range and velocity measurements in the presence of multiple targets. Examination of the underlying mathematics has shown that the generation of a considerable number of ghost targets is inevitable, their motion is very target-like and ghost returns will correlate scan-to-scan to form tracks of significant length.

A method to help mitigate the problems with the ghost tracks has been found where an extended PRI set is used to cause the ghost positions to move in a cyclic manner. If the cycle time of the extended PRI set is longer than the association window of the tracker, then the ghost locations appear de-correlated to the tracker and ghost tracks are less likely to be formed.

Previous work on applying Evolutionary Algorithms to the problem of PRI set optimisation [9] is applicable to the optimisation of multiple PRI sets that can be used with a rolling PRI system.

Acknowledgements

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References

1. William H. Long and Keith A. Harringer, "**Medium PRF for the AN/APG-66 radar,**" *Proceedings of the IEEE*, vol. 73, no. 2, pp. 301–311, Feb. 1985.

2. J. Simpson, "**PRF set selection for pulse Doppler radars**," *IEEE Region 5 Conference, 1988: 'Spanning the Peaks of Electrotechnology'*, 1988, pp. 38–44.

3. Eric W. Weisstein. "**Chinese Remainder Theorem**." From *MathWorld*--A Wolfram Web Resource. http://mathworld.wolfram.com/ChineseRemainderTheorem.html

4. Planetmath.org http://planetmath.org/encyclopedia/ChineseRemainderTheorem.html

5. A.G. Thomas, M.C. Berg, "**Medium PRF set selection: an approach through combinatorics**.", *IEE Proc.-Radar, Sonar Navig.*, Pages 307- 311, Vol. 141, No. 6, December 1994

6. A.M. Kinghorn and N.K. Williams, "**The Decodability of Multiple-PRF Radar Waveforms**", *Proc IEE International Radar Conference*, Edinburgh, 1997

7. E.J. Hughes and M. Lewis, "**Improved Detection and Ambiguity Resolution of Low Observable Targets in MPRF Radar",** *EMRS DTC 2nd Annual Technical Conference*, Edinburgh, June 2005

8. E.J. Hughes and M. Lewis, "**An Intelligent Agent Based Track-Before-Detect System Applied to a Range and Velocity Ambiguous Radar**", *EMRS DTC 1st Annual Technical Conference*, May 2004

9. C.M. Alabaster, E.J. Hughes and J.H. Matthew, "**Medium PRF Radar PRF Selection Using Evolutionary Algorithms"**. *IEEE Transactions on Aerospace and Electronic Systems*, pages 990-1001, Vol. 39, No. 3, July 2003

10. Zalzala, A. M. S., and Flemming, P. J. (Eds.) (1997) *Genetic Algorithms in Engineering Systems*. London, The Institution of Electrical Engineers, 1997.

11. Goldberg, D. E. (1989) *Genetic Algorithms in Search, Optimization, and Machine Learning*. Reading, MA: Addison-Wesley, 1989.